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Wolfsburg Working Papers No. 11-04

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The Impact of Communication Topologies on Prices

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Abstract

We investigate the impact of agent communication networks on prices in an artificial stock market. Networks with different centralization measures are tested for their effect on the volatility of prices. Trading strategies diffuse through the different network topologies, mimetic contagion arises through the adaptive behavior of the heterogeneous agents. Short trends may trigger cascades of buy and sell orders due to increased diffusion speed within highly centralized communication networks. Simulation results suggest a correlation between the network centralization measures and the volatility of the resulting stock prices.

Keywords:

Microsimulation, Financial Markets, Network Topologies, Mimetic Contagion, Herd Behavior

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1. Introduction

Mimetic behavior or herding by investors is a widely discussed phenomenon (Hirshleifer and Teoh, 2003) that has already found its way into the micro-simulation of stock markets models. Inspired by the superior profits of competing market participants, agents decide to disregard their own signals when trading stocks and mimic the behavior of potentially more successful direct neighbors instead. The stock market simulation models of Cont and Bouchaud (2000) and Lux and Marchesi (2000) incorporated that property in form of clustered agents that act in concert. We want to extend that line of research by introducing direct agent communication within several types of communication network topologies.

Within the last 10 years the research on networks has discovered new network models that matched the properties of empirically found networks closer than random networks (Dorogovtsev and Mendes, 2003). It can no longer be assumed that complex networks like social networks resemble the often used random networks introduced by Erdös and Renyi (1959). Small-world networks (Watts and Strogatz, 1998) and scale-free networks (Barabasi and Albert, 1999) have not only proved to resemble real life networks (Wang and Chen, 2003), but exhibit different properties with regard to information diffusion (Pastor-Satorras and Vespignani, 2001).

When combining the simulation of artificial stock markets and information diffusion with different communication network topologies, the question arises: What influence do different network topologies have on the time series of resulting stock prices? Earlier stock market models did not address this subject because of the lack of direct agent communication and the lack of different communication network topologies. We will show that topology influences the outcome of a stock market simulation and has interesting implications.

The use of simulation models has a long tradition in decision support systems

(Arnott and Pervan, 2008). With increasing computing power, agent-based simulations have been established more and more in the simulation domain (LeBaron, 2006). Such agent-based models have several advantages compared to classical simulation models, especially in replicating complex systems with heterogeneous actors (Hommes, 2006). Agent-based models are particularly suited for simulation models when an auction mechanism is used to find market prices (Sikora and Sachdev, 2008; Bandyopadhyay et al., 2006). The simulation of an artificial stock market can therefore be useful in terms of decision support in two ways:

- The system can be used by public decision makers to investigate critical market situations and their consequences on the economic development.

- The simulation offers the opportunity for private decision makers to check the consequences of various market constellations on the return on investment and risk associated with their investment strategy.

Creating artificial stock markets already has a more than 10 year history. They may be one of the few ways to study complex interdependent non-linear price dynamics that can be observed by empirical research. With the help of artificial markets like the ones found in Lux and Marchesi (2000), Cont and Bouchaud (2000), Bak et al. (1997) and the Santa Fe Artificial Stock Market (LeBaron et al., 1999), to name just a few, new insights have been found into how the stylized facts of the capital markets (Cont, 2001) may arise. Modeling agent behavior on the micro level and exploring the consequences on the macro level of the resulting time series of prices is one of the main tasks when creating artificial stock markets. Andrew Lo recently introduced the Adaptive Market Hypothesis (AMH), that may have the potential not only to provide a theoretical framework for artificial stock markets, but may even have the potential to reconcile the idea of efficient markets with behavioral biases (Lo, 2004).

The *Santa Fe Artificial Stock Market* (SFASM) (LeBaron et al., 1999) was one of the earliest publicly available artificial stock markets.[1] The agents generate their orders by using a pool of $R = 60$ available rules. Based on a *classifier system* and a *genetic algorithm*, learning and adaption is possible. Direct communication between the agents is not possible.

The *Bak-Paczuski-Shubik* model (Bak et al., 1997) has N agents and $N/2$ shares, therefore half of the agent population are potential buyers and half of the population are potential sellers. Of the N agents, $(N - K)$ agents are trend traders and K agents are fundamental agents. Of these $(N - K)/2$ trend traders and $K/2$ fundamental traders own shares. Agents not owning shares receive a fixed rate of interest i on their deposit.

Cont and Bouchaud (2000) suggest a model of an agent based financial market with agents exhibiting herding behavior. Large fluctuations of the agents aggregated demand seem to lead to heavy tails in the distribution of returns. Cont & Bouchaud assume that the reason for the fluctuations can be found in the interaction and imitation of the market participants that coexist in a random communication network. N agents decide on individual random variable $\phi_i \in \{+1, -1, 0\}$, $\phi_i = +1$ to either buy (+1), sell (-1) or to be inactive (0). The aggregate excess demand is then defined as:

$$D(t) = \sum_{i=1}^{N} \phi_i(t) \tag{1}$$

Agents are grouped together in clusters, all members of a cluster sharing the same belief and therefore having the same demand ϕ_i. If W_α is the size of cluster α and $\phi_\alpha(t)$ is the common decision to buy sell or to be inactive at time t, the joint

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[1] It can still be downloaded at: http://sourceforge.net/projects/artstkmkt/

demand for cluster α follows as $\phi_\alpha(t)W_\alpha$.

The Lux and Marchesi (2000) model divides N speculative traders at time t into two groups: fundamentalists n_t^f and chartists n_t^c with $n_t^f + n_t^c = N$. Chartists are further differentiated into two subgroups: optimistic n_t^+ and pessimistic n_t^- with $n_t^+ + n_t^- = n_t^c$. The sentiment among the chartists is represented by an opinion index. The opinion index is accessible to all chartists and influences their trading decision next to the price trend.

Hein et al. (2007) showed with an earlier version of the Frankfurt Artificial Stock Market (FASM) that a small-world inter-agent communication network influences the resulting time series of prices. With an increasing rewiring probability for the small-world network, increasing volatility and distortion of resulting prices is observed. The results have encouraged us to further search for a system-inherent network effect that may have a substantial effect on the outcome of an artificial stock market.

Kirman (2002) suggested direct agent interaction for artificial stock markets. Baker (1984) showed that social structural patterns influence price volatility. We would like to follow up on these ideas by exploring the consequences of different communication network topologies. The influence of network topologies on economic decisions has been studied before by Wilhite (2006). It was found that the network topology, like scale-free, small-world, star and other topologies, affects the outcome of economic games and exchange. The new version of the FASM now specifically targets the question of how networks used for inter-agent communication in general affect the market behavior. Several model changes have been necessary to accomplish this task. A new agent type, namely the retail agent, has been introduced and activation thresholds similar to Granovetter (1978) added. To categorize networks the concept of *network centralization* (Freeman, 1978/79) has been chosen.

Several stock market crises may have something in common, as rumors travel like an infectious disease through a communication network of market participants and influence the behavior of traders (DiFonzo and Bordia, 1997). Within that scenario the newly introduced retail agent plays an important role. The idea of introducing retail agents was partly stimulated by the empirical evidence of Kumar and Lee (2006). Retail agents are not endowed with a trading strategy and are initially inactive. They only monitor market performance and become activated as soon as a minimum profit within a time window is reached. Once activated they look out for profitable trading strategies in their direct neighborhood. If a neighbor owns a strategy and it is profitable, retail agents imitate that strategy and start trading. If a threshold of negative performance is reached, they sell their shares and fall into hibernation for a number of trading days. The whole cycle starts again when the hibernation is over and the performance threshold at the stock exchange is reached again. With the help of such mechanisms the number of participating agents during the course of a simulation varies and the ups and downs of the exogenous inner value may be exaggerated. As a result of the expanding and contracting numbers of market participants the topology of the agent communication network influences how information is spread. The existence of mimetic contagion caused by the retail agents in combination with the network topology leaves a characteristic signature within the time series of resulting prices. Centralization in this context may be an important factor since the distribution of information within a network is improved by centralization (Pastor-Satorras and Vespignani, 2001). Profitable agent behavior like buying and selling within short price trends are communicated faster in centralized networks, a cascade of buy and sell orders may be the consequence that will lead to large price swings. Less centralized communication networks showed that they were much less able to distribute profitable agent behavior quick enough to trigger cascades of buying and selling orders.

6

A tendency towards centralization may be observed within our financial system. The banking industry is creating large organizations by mergers and acquisitions, hedge funds are able to influence stock prices with increasing amounts of capital, the media distribute the opinions of analysts that tend to herd (Welch, 2000) to almost every market participant. This inherent property of increasing centralization may have unwanted side effects that may lead to excess volatility.

The following section briefly describes the network topologies and network centralization measures used. Section 3 introduces the new version of the FASM with focus on the recently included retail agents and the diffusion algorithm and auction method used. The simulation setup with all parameters is presented in detail in section 4 before section 5 discusses the results of the simulation runs in relation to the different network topologies used.

2. Communication Networks

The next subsections introduce briefly the concepts of network topologies and network centralization as they will be needed as input parameter and classification measures for the simulations. Please refer to Dorogovtsev and Mendes (2003) and Wasserman and Faust (1994) for further studies.

2.1. Random Networks

Since the seminal paper of Erdös and Renyi (1959), the random network theory has dominated scientific thinking (Barabasi, 2003). Real world networks had been thought to be too complex to understand and therefore held to be random. In the absence of other well-understood network models, random networks, also called ER-networks, were widely used when modeling networks.

The process of creating an ER-network depends on probability p. For a network with n nodes each possible pair of distinct nodes are connected with an edge with

7

probability p. An ER-network has the property that the majority of nodes have a degree that is close to the average degree of the overall network and that there is not much deviation from the average below and above it. It has been shown that the distribution of links follows a Poisson-Distribution.

2.2. Small-World Networks

Small-world networks have their roots in social networks, where most people are friends with their immediate neighbors, but also with a few friends who are far away (Watts and Strogatz, 1998).

The network topology of small-world networks interpolates between regular and random graphs. Starting from a completely regular graph, where each node has four links to its direct neighbors , a rewiring procedure with probability p takes place. With higher p's more and more links are redirected until a random graph emerges. Watts and Strogatz define a network to be a small-world network if the average path length d is comparable to a random graph and the clustering coefficient C is much greater than for a random graph.

2.3. Scale-Free Networks

When Albert et al. (1999) started to map the Internet, they did not know that they were about to influence network research in a sustained way. Because of the diverse interests of every Internet user and the gigantic number of web pages, the linkages between web pages were thought to be randomly linked as a random network. The results of their study have disagreed with this expectation in a surprising way. Only a few pages have the majority of links, whereas most pages are only very sparsely connected. More than 80% of all pages visited have 4 links or fewer, only 0.01% of the pages are linked to more than 1,000 other pages (some up to two million). The probability distribution function $P(j)$ of the degree j of scale-free networks is described by:

$$P(j) \approx j^{-\gamma} \qquad (2)$$

with $j > 0$ and $\gamma > 0$, γ called the *scale-free exponent* or *degree exponent*.

2.4. Network Centralization

Within social networks centrally positioned individuals are seen as having influence (Wasserman and Faust, 1994) on others. For the classification of networks in terms of centralization, Freeman (1978/79) defined three centralization measures: *degree centralization*, *closeness centralization* and *betweenness centralization*. With the help of these network centralization measures, networks may be classified and differentiated. With the availability of the centralization measurements, networks may be taken as input parameters for our simulation model and analyzed in terms of how their topology affects market behavior.

2.4.1. Degree Centralization

Degree centralization measures the variation of the degree of a network member in relation to all other network members. It shows how relatively well connected a node is. For g nodes with n^* being the node with the highest degree and C_D^i equaling the degree (amount of links) of node i, the degree centralization is defined as (Freeman, 1978/79):

$$C_D = \frac{\sum_{i=1}^{g} \left[C_D^{n^*} - C_D^i \right]}{[(g-1)(g-2)]} \qquad (3)$$

Degree centralization varies between 0 and 1. The star network has a degree-centralization of 1.

9

2.4.2. Betweenness Centralization

Interactions between two nonadjacent nodes A and B depend on other nodes that exist on the path from node A to node B. The betweenness centralization measures the frequency of a node appearing on the path between the two nonadjacent nodes in relation to the other nodes of the network. For g nodes with n^* being the node with the highest betweenness and s_{jk} equaling the amount of shortest paths between nodes j and k. $p_{jk}(i)$ equals the probability that node i is on the path between node j and k. The betweenness centralization for a network is defined as (Freeman, 1978/79):

$$C_B = \frac{2 \sum_{i=1}^{g} \left[C_B^{n^*} - C_B^i \right]}{\left[(g-1)^2 (g-2) \right]} \qquad (4)$$

Betweenness centralization varies between 0 and 1, and reaches a maximum if a node is on all the shortest paths between all other nodes (star network).

2.4.3. Closeness Centralization

Closeness centralization measures how close a node is to the other nodes of a network in relation to the other nodes of the network. It shows how quickly (shortest paths to other nodes) one node can be reached from other nodes. With $d(i, j)$ being the distance (length of the shortest path) between node i and j. The closeness centralization for a network with g nodes and n^* being the node with the highest closeness is defined as (Freeman, 1978/79):

$$C_C = \frac{\sum_{i=1}^{g} \left[C_C^{n^*} - C_C^i \right]}{\left[(g-1)(g-2) \right] / (2g - 3)} \qquad (5)$$

Closeness centralization varies between 0 and 1. The star network has a closeness centralization of 1.

3. The Frankfurt Artificial Stock Market

The Frankfurt Artificial Stock Market (FASM) has been designed to study how different communication network topologies affect the properties of the resulting time series of prices (Hein et al., 2005). Two types of trading strategies, namely the fundamental strategy and the trend oriented strategy, as used in other models (Hommes, 2006), propagate according to their actual performance through a communication network. The number of agents applying one of the strategies varies according to the profitability of the strategies. The course of the price building process depends on the inner value of the stock and on the number of agents using the trend or fundamental strategy.

This section introduces the new version of the FASM. The major components namely agent behavior, the auction method and the communication mechanism will be discussed. For a more in depth comparison of the preceeding stock market models please refer to Hommes (2006) and LeBaron (2006).

3.1. Agent Behavior

In addition to the two traditional agent types *fundamental* and *trend*, we are using a new kind of agent, calling it *retail agent*. The intention is to model the vast numbers of uninformed and mostly inactive investors that may play a role, especially in extreme valuation situations. To the knowledge of the authors, there is no empirical data yet that describes the behavior of such investors. Kumar and Lee (2006) showed that individual investors tend to act in concert and that a relation between sentiment and return formation exists. Nevertheless, introducing a retail agent to the FASM was more the consequence of personal observations of the authors. Alternative ways to decribe agent behavior may be found for example in Chen and Yeh (2001).

11

3.1.1. Retail Agents

The retail agent is endowed with the ability to adopt both strategy types and acts on activation threshold, while initial trend and fundamental agents never switch their strategy. As for most retail investors stock market transactions are mostly only a secondary income stream, it should be possible to refrain from transactions if experience suggests this. Therefore, retail agents are initially inactive and without a trading strategy. Rising prices beyond a certain threshold will activate them and prompt them to participate in trading. Retail agents will then start to look out for promising trading strategies within their direct neighborhood.

Three cases are possible:

1. All direct neighbors are retail agents, none of whom has yet acquired a trading strategy.
2. One of the direct neighbors has a trading strategy, that was successful within a specific time frame.
3. Several direct neighbors are using different trading strategies.

In the first case the retail agent remains active, but refrains from trading, because of the lack of any trading strategy. In the second case, there is one agent in the direct neighborhood with a trading strategy. If the strategy has been successful within a time window, the agent adopts the new strategy and starts trading. In the third case there are multiple strategies within the direct neighborhood. In that case the most successful strategy will be adopted and the agent starts trading.

Retail agents are initially not endowed with a trading strategy. They copy the behavior from adjacent fundamental and trend agents (please refer to section 3.1.2) that populate the network which is dominated numerically by inactive retail agents. Fundamental and trend agents never change their strategy and are always active, as would be expected from institutional investors. Kumar and Lee (2006) found in

12

their study that the average trade size of over 60,000 retail investor households is about 9,000 US\$. We assumed that the trading volume caused by institutional investors by far exceeds the trading volume caused by individual retail investors.

In the course of the simulation the two clusters of fundamental and trend strategies expand and contract their size depending on the deployment of the price building process. They may touch and may conquer the whole network. Once activated, retail agents may change their type depending on the success of their direct neighbors. If the direct neighbor reported a superior performance several times, the agent adapts its behavior to the strategy of the neighbor. Successful strategies diffuse through the communication network and influence the development of prices.

The contraction in the size of the clusters may be initiated by fundamental agents buying or selling in case of a larger mispricing (over- or undervaluation) in relation to the inner value p^f (p^f will be defined in section 3.1.2). This counter movement of the price might establish a down trend that is enforced by trend agents. The retail agents have been modeled in such a way that if the actual price falls below of the deactivation threshold, retail agents start selling their shares and stop trading for a number of days. They switch to an inactive status for an individual number of days, before they start monitoring the share prices again. They fall back into their initial state, and only the amount of cash differs. The activation and deactivation thresholds have been chosen to be asymmetrical (table 2) since investors tend to realize profits too early and let losses run for too long (similiar to the value function of the prospect theory (Kahneman and Tversky, 1979)). Depending on the development of the stock price and the trading strategies used during the activity period, it seems to be probable, that retail agents will end their activity cycle with a cash loss. Empirical evidence from Odean and Barber (2007) shows that retail investors in Taiwan lost on average 2.8% of personal income when trading on the Taiwan stock exchange. Table 7 will show that retail agents lose cash over

the course of a simulation. The activity cycle of an retail agent starts again, if the personal activation threshold is reached.

3.1.2. Fundamental and Trend Agents

Trend agents (also may called noise traders) and fundamental agents are defined in a way analogous to other stock market models (see Hommes (2006) for an overview). Both agent types are unable to change their type: only retail agents may change their type several times during their activity cycle.

Fundamental agents observe an inner value p^f that is flawed by a small random number for each fundamental agent to avoid an unrealistic perfect knowledge of p^f. The inner value is a random walk with a daily standard deviation of, for example 1%. Fundamental agents are heterogeneous in the sense that they possess different wealth consisting of stocks and cash and have different risk premiums.

Furthermore, fundamental agents are aware of the existence of trend agents participating in the market and the associated over- and under-valuations. During periods of large misvaluations they are able to extend their risk premiums in several steps. During periods of low volatility they are able to reduce their risk premiums to their initial level. Fundamental agents assume that the price will sooner or later return closer to the inner value, but are aware of possible misvaluations where it might be profitable to modify the individual risk premium in the direction of the ongoing trend.

The number of shares traded per agent is threshold dependent; the greater the mispricing the greater the numbers of shares ordered. The agents are able to generate limit orders and market orders, as is necessary due to the batch limit order book that is used for an auctioneer (refer to section 3.2). Every day each fundamental agent k creates one buy order with limit $p^f - \gamma_k$ and one sell order with limit $p^f + \gamma_k$. If the current price leaves that corridor an order may be filled depending

on other orders within the order book during the daily settlement. For example, with an individual risk premium γ of 3% (table 1), a difference of more than 3% between the stock price and the inner value p^f is needed to fill buy or sell orders. Increasing over- or under-valuations activate more and more agents to participate in the trading. The fundamental agents are endowed with substantial amounts of wealth to hold the price close to the inner value p^f. Short selling and lending is not allowed, and if an agent runs out of cash or stocks an order can not be created until sufficient funds are available.

Trend agents base their trading decisions solely on historical price patterns (moving averages of prices). They are heterogeneous in the sense that they hold different wealth and own an individual duration of the moving average (e.g. x days moving average). Once the price breaks through the agent's individual moving average from below (above) buys (sells) are initiated. The presence of individual moving averages may lead to a situation where cascading buying or selling decisions of the part of trend agents may arise. The buying decision of one agent may trigger the buying decision of another agent with a slightly longer moving average (like in Granovetter (1978)). Trend agents create order limits based on the price of the previous trading day modified by a small random number. The sign of the random number depends on the additional information issued by the auctioneer described in 3.2. The probability of a negative sign is higher if there have been more sell orders than buy orders at the last fixed price and vice-versa.

Example for the order creation of fundamental and trend agents: $p = 1,053, p^f = 1,000$, individual risk premium of fundamental agent k: $\gamma_k = 1,5\%$ (table 1), individual time window of trend agent: 20 days (table1), 20-day-moving-average price = 1,010:

Order generation of the fundamental agent: Each fundamental agent creates one sell and one buy order every day: Buy order: Buy limit $= p^f - 1,5\% = 985$,

Buy volume = 2 shares since the price is above the limit (not attractive)(see table 3 for quantities). Fundamental agent buy order: Buy 2 shares at limit 985. Sell order: Sell limit = $p^f + 1,5\% = 1,015$, sell volume = 5 shares, since the price is $3,74\%$ above the sell limit. It is attractive to sell more (see table 3 for quantities). Fundamental agent sell order: Sell 5 shares at limit 1,015.

Order generation of the trend agent: Each trend agent creates one order every day: The price is above the moving average, a buy order is created. The buy limit is at $p = 1,053$ plus or minus a small random number, for example $1,045$. Buy volume = 3 shares, since the price is 3,46% above the moving-average price. Because of the strong trend it seems attractive to buy more (see table 3 for quantities). Trend agent order: Buy 3 shares at limit 1,045.

3.2. The Auction Mechanism

The FASM uses a *batch limit order book* which is settled once a day like in Hussam et al. (2008). All agents supply their limit orders to the central auctioneer or refrain from trading. The auctioneer settles the price at the maximum possible trading volume by matching compatible buy and sell orders. Since the agents are not allowed to look into the order book the auctioneer creates additional information revealing how balanced the order book is. If there have been more buy than sell orders for the fixed price a "G" for Geld (Money) will be issued, vice versa a "B" for Brief (shares) will be issued. This additional information plays a role in the way trend agents find their order limit, as described in 3.1.2. The batch limit order book is still used for odd lots at the Frankfurt Stock Exchange. It has been shown that the auction mechanism influences the price building process. The market microstructure aspects of artificial stock markets is still an underdeveloped field that will gain more attention as the artificial market models mature. Refer to Garman (1976) for an introduction to the field of market mircostructure theory. In-

16

teresting more recent articles are Mendelson (1987), Weber (1999), Clemons and Weber (1997) and Weber (1995). Different auction mechanisms for artificial stock markets have been reviewed by Pellizzari and Dal Forno (2007). It is planned to implement other auction mechanisms within future versions of the FASM.

4. Simulation Setup

The simulations were accomplished using 500 agents that were initially divided into 29 fundamental and 18 trend agents, 453 retail agents and one random trader. In the case of no activated retail agents fundamental agents are in the majority to stabilize the price against the trend agents. The random trader randomly buys and sells small amounts of shares to assure market liquidity. An exogenous inner value p^f for 3,000 trading days was generated. p^f starts with a value of 1,000 and has a daily standard deviation of 0.9% (table 4). Each agent is endowed with a random number of cash and stocks as initial wealth (table 1). The random numbers for this wealth are limited within upper and lower bounds. The communication probability for each agent has been set to 4%, which means that each agent communicates on average about every 25 days with its neighbors. Fundamental agents may buy between 2 to 80 shares per order and trend agents 1 to 20 shares per order depending on the deviation from their activation thresholds (table 3). The greater order volume of fundamental agents for buy and sell orders generates pressure on the stock price to return to a state closer to its inner value in the case of a larger difference between price and inner value.

Retail agents are activated when the price increase exceeds an activation threshold that is individually set for each agent. The activation threshold is randomly generated in the range of 5% to 10%, the deactivation threshold is randomly generated in the range of 10% to 18%. Price changes are computed within a time

17

agents' parameters					
agent type	#	γ	time window	init. cash	init. stocks
fundamental	29	$0.5\% - 3.5\%$	$-$	$5 - 8$ mil.	$5,000 - 8,000$
trend	18	$-$	$10 - 70$ days	$1 - 2$ mil.	$2,000 - 3,000$
retail	453	$-$	$-$	$1 - 1.5$ mil.	0

Table 1: Parameter values of fundamental and trend agents

retail agents' specific parameters				
activation thresholds	deactivation thresholds	deactivation periods	profit windows	sell period
$5\% - 10\%$	$10\% - 18\%$	$60 - 90$ days	$20 - 40$ days	10 days

Table 2: Retail agents' specific parameters

window which varies between 20 to 40 days per agent (table 2). The activation and deactivation bounds depend on the inner value. An inner value with a smaller standard deviation needs smaller bounds for activation, otherwise no activation of retail agents would be possible. Retail agents are inactive for at least 60 to 90 days after deactivation and need at least 10 days for the liquidation of their portfolio (table 2). A liquidation of all retail agent's portfolios within a day would be beyond the buying capacity of fundamental agents. The parameter setup with different kind of random variables makes it very improbable that two agents will share the same parameters.

The last and most important parameter is the communication network type that connects the agents and allows communication with their nearest neighbors. Four network topologies have been chosen: a random network, a small-world network, and two scale-free networks with different centralization measures. Since the intro-

fundamental agents		trend agents	
deviation from signal	vol. in shares	deviation from signal	vol. in shares
$0\% - 2\%$	2	$0\% - 2\%$	1
$2\% - 5\%$	5	$2\% - 4\%$	3
$5\% - 10\%$	15	$4\% - 7\%$	5
$10\% - \infty$	80	$7\% - \infty$	20

Table 3: Volume of shares ordered by fundamental and trend agents depending on the strength of the buy/sell signal

P_0^f	σ	μ	# of trading days
$1,000$	0.9%	0	$3,000$

Table 4: Parameters for the generation of fundamental value time series parameters

duction of scale-free networks many variations of scale-free generating algorithms have been introduced. They mostly differ in preferential attachment probability. The networks were generated with Pajek 1.21.[2] and NetMiner 3 [3]. For the two scale-free networks, two different generating algorithms were used (Pajek and Net-Miner) leading to two scale-free networks with different centralization measures. The agent types were placed arbitrarily within the networks. Figure 1 presents a small-world network with 100 nodes as an example of how the agent types were distributed. The original networks with 500 nodes are inconvenient for demonstration due to the large number of edges. Each network consists of 500 nodes and 1,000 edges. The networks only differ in the way the edges are distributed among the nodes.

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[2] free for download at http://vlado.fmf.uni-lj.si/pub/networks/pajek/
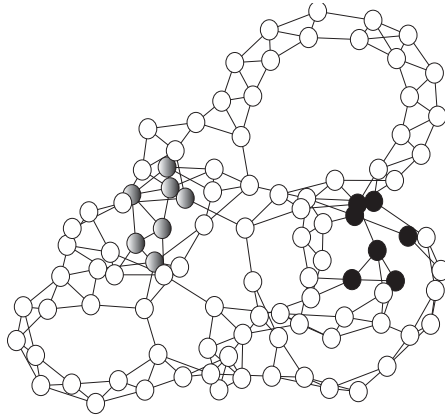[3] www.netminer.com

Figure 1: Example of a small-world network with 100 nodes (black: trend agents, gray: fundamental agents, white: retail agents)

Network Types	Betweenness Centralization	Closeness Centralization	Degree Centralization
Random	0.0306	0.0994	0.0121
Small-World	0.0461	0.0672	0.0040
Scale-Free 1	0.4048	0.3520	0.1067
Scale-Free 2	0.4574	0.5930	0.6841

Table 5: The centralization measures of the four used networks. The scale-free 1 network shows a higher degree of centralization than the random and the small-world network in all three measures of centralization. The scale-free 2 network exhibits the highest degree of centralization of all networks. There is no correlation between them since they measure different aspects of centralization. Therefore the random network is the least centralized and the scale-free 2 is the most centralized network.

The network centralization measures for the four network types are shown in table 5. Closeness and degree centralization figures increase from the small-world to the scale-free network. The centralization measures in table 5 are sorted in increasing order from the small-world to the scale-free network. Since these centralization measures are not correlated, all three measures are used in parallel.

For each network 10 simulations with identical parameters were conducted to indicate the impact of the random variables on the simulation results. The variance of the results did not change much with more simulation runs per network.

5. Results

Figure 2 presents a simulation run for the small-world communication network. The charts for the other networks are available online.The price chart in figure 2 (first chart) exhibits frequent periods of upward and downward trends that coincide with the activation of the retail agents as shown in figure 4. An increasing number of agents using the trend strategy (fig. 4, lower chart, dotted line) move the price away from its inner value. In this situation, given the design of the simulation model, fundamental agents react to the investment opportunity with higher order volumes. They sell more shares in the case of increasing over-valuations, they buy more shares in the case of increasing under-valuations. The sharp drops of the price in figure 2 (first chart e.g. around trading days 400 or 800) are initiated by the deactivation of retail agents, when they sell their portfolio of shares.

We conducted 10 simulation runs per network. Table 6 summarizes the average values of the 10 results. The standard deviation in table 6 increases with the order of the networks used (random, small-world, scale-free 1, scale-free 2). The skewness and the minimum return decrease with the order of the networks. The kurtosis of the times series of prices indicates a leptokurtic shape of the re-
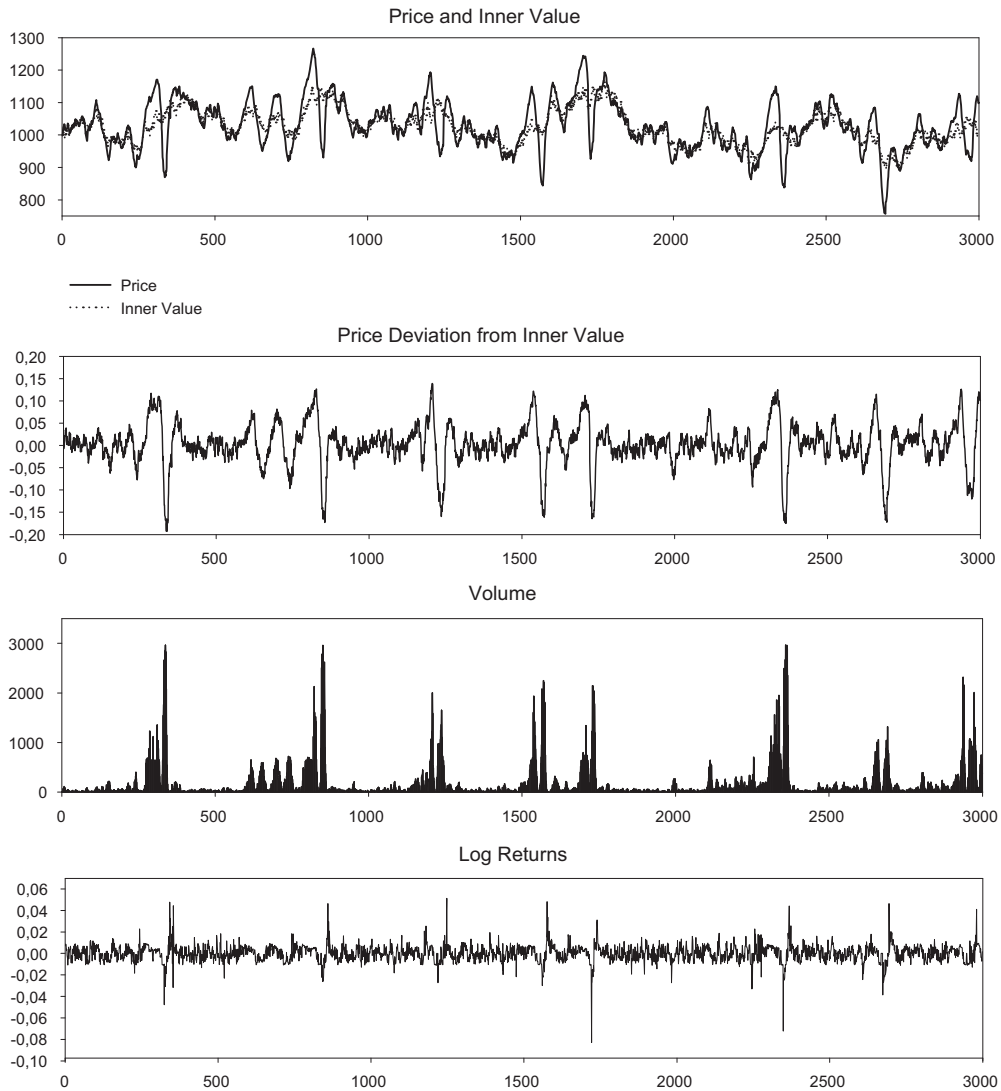
Figure 2: Simulation results using the small-world communication network. The top chart displays the price and exogeneous inner value used. The chart below shows the precentaged difference between the price and the inner value. There are periods of low deviation between price and inner value and sudden periods of large deviations. The third chart depicts the volume of shares traded. The corrleation of high deviations in the second chart and high volume in the third chart is obvious. The bottom chart shows daily returns, relatively quite periods are suddenly interrupted by short periods of high volatility.
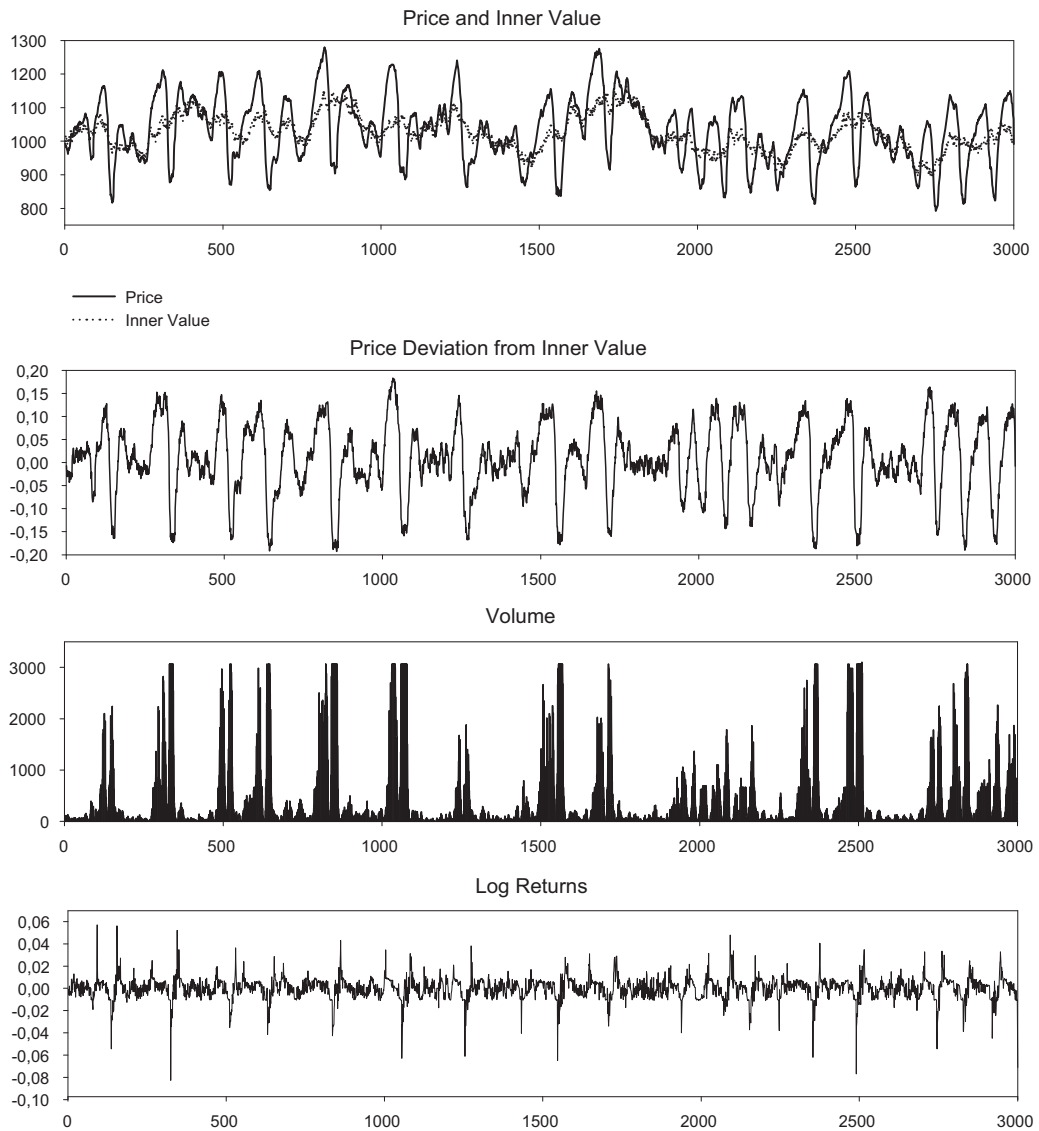
22

Figure 3: Simulation results using the scale-free 2 network. The most obvious differences to the small-world network simulation results are the greater deviations between price and inner value and higher volume correlated to periods of extensive volatility. The periods of high volatility and volume occur more often than within the small-world network simulation. Apart from the communication networks all other parameters of the simulations stayed the same.

23

turn distributions. The Hill-Estimators (Lux, 2001) are within the area of empirical observations for real markets (Gopikrishnan et al., 1998). The augmented Dickey-Fuller tests (Dickey et al., 1986) in table 6 confirm the hypothesis that the time series of stock prices for all networks are non-stationary. The time series of stock prices of real markets proved to be non-stationary (Lux and Marchesi, 2000).

Number of Retail Agents

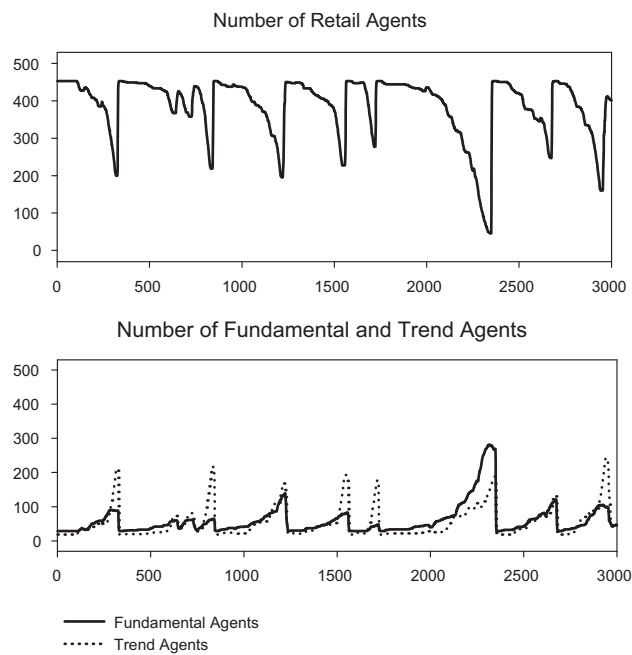Number of Fundamental and Trend Agents

Figure 4: Results for the group sizes of retail, trend and fundamental agents using the small-world network

Our model is in accordance with the weak form market efficiency since trend investors realize on average negative trading results over longer simulation runs (table 7). Fundamental investors usually end within the positive territory. The 4th statistical moment of returns increase from less to more centralized networks. The higher diffusion speed within centralized networks leads to larger quantities of trend investors during short trends. The price deviates from the inner value, which

presents arbitrage possibilities for fundamental investors. Since the fundamental investors are able to order larger quantities of stocks, the price will sooner or later return closer to the inner value. In consequence trend investors will on average loose and fundamental investors will on average gain from that behavior. The negative 3rd statistical moment stands in relation with the behavior of the retail investors. As soon as large losses are encountered, retail investors panic and flee the market. They sell all their shares within a short period of time and cause large moves to the downside.

Volatility and distortion numbers will be discussed later in relation to network centralization measures. The volume of shares traded increases with the order of the networks. Networks with higher centralization measures lead to higher volumes over the course of the simulation. A potential explanation for this behavior is, that centralized networks exhibit a faster diffusion speed (Pastor-Satorras and Vespignani, 2001). This leads to greater differences between inner value and stock price, which causes higher turnover.

Table 7 presents the profit numbers for the agent types used in our model. The profit numbers are computed over the whole simulation run. The profit numbers are averaged over 10 simulation runs and are averaged within the type groups. Increased network centralization causes higher profits for fundamental agents, because of higher differences between price and inner value, and higher losses for trend and retail agents, even though retail agents are not always active.

The resulting time series of stock prices are analyzed with respect to volatility and to distortion of p^f. Figure 5 depicts the volatility (box-plots) and the centralization measures of the four networks used (line plots) for ten simulation runs per network. The box-plots show the range of volatility for ten time series of prices. Table 6 (section D) presents the exact values for the average volatility.

A. Descriptive Statistics

	Random	Small-World	Scale-Free 1	Scale-Free 2
No. of Observations	3,000	3,000	3,000	3,000
Mean	0%	0%	0%	0%
Standard Deviation	0.74%	0.78%	0.83%	0.91%
Skewness	-0.54	-0.21	-0.56	-0.96
Min.	-5.32%	-7.45%	-8.48%	-13.22%
Max.	5.63%	5.26%	5.60%	7.35%

B. Fat Tail Property

	Random	Small-World	Scale-Free 1	Scale-Free 2
Kurtosis	10.95	8.18	11.36	14.70
Hill-Estimator (5% tail)	5.4	5.2	4.9	4.8

C. Unit Root

	Random	Small-World	Scale-Free 1	Scale-Free 2
ADF-Test:				
Test critical values:				
1% level:	-3.43	-3.43	-3.43	-3.43
5% level:	-2.86	-2.86	-2.86	-2.86
10% level:	-2.56	-2.56	-2.56	-2.56
ADF	-16.45	-16.60	-14.46	-14.57

D. Volatility, Distortion and Volume

	Random	Small-World	Scale-Free 1	Scale-Free 2
Volatility (average)	55.46	60.43	68.31	82.32
Distortion (average)	2.72	3.47	3.66	4.37
Volume in shares	443,375	568,299	691,699	1,133,726

26

Table 6: Average statistic numbers for 10 simulation runs with identical parameters

E. Agent Type Performance				
	Random	*Small-World*	*Scale-Free 1*	*Scale-Free 2*
Fundamental	10.53%	13.57%	17.14%	34.91%
Trend	-11.39%	-15.03%	-18.93%	-19.12%
Retail	-6.60%	-8.07%	-11.36%	-22.65%

Table 7: Agent type performance

Our results indicate that there is a relation between increased network central-ization and volatility. Centralized nodes (agents) have the ability to spread prof-itable trading strategies much faster than nodes in the periphery of a network. The adaption of the trader community to a newly established trend takes place in a shorter time frame. In centralized networks short trends in the inner value may already be able to trigger cascading buy or sell orders, whereas this is not the case in less centralized networks. An over- or undervaluation with respect to the inner value can be observed in higher frequencies than is the case for less centralized networks.

Our results indicate that the topology of an agent communication network with bounded rational and heterogeneous traders impacts on the resulting time series of stock prices. Higher centralization of the agent communication networks leads to a rise in volatility of the stock prices. The sharp increase in volatility and dis-tortion for the small-world network in figure 5 without a simultaneous increase in centralization may be a result of the small-world effect (Dorogovtsev and Mendes, 2003). The rate of diffusion for the trading strategies in a small-world network is

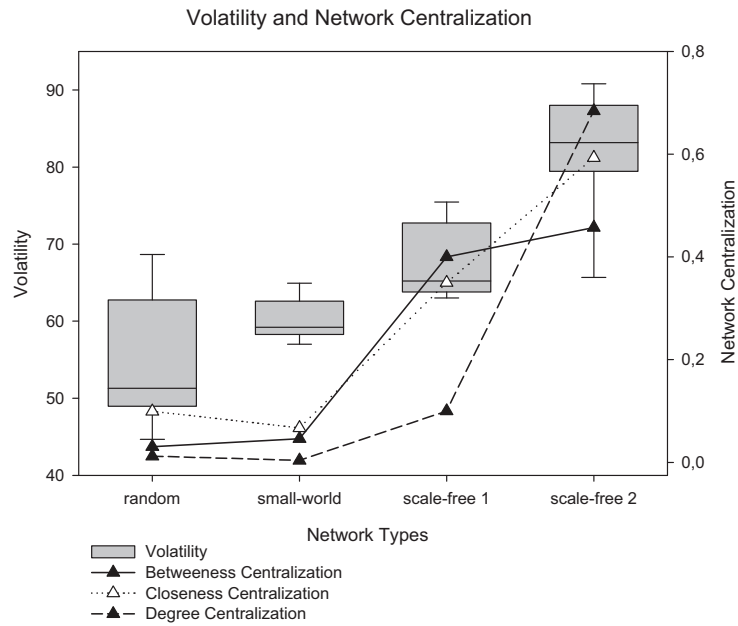higher than the rate of diffusion in a random network that has similar centralization measures.

Figure 5: Results for the volatility in relation to network centralization. Higher network centralization goes along with higher volatility. Our results indicate that agent communication networks with less or no large hubs are favorable when market volatility needs to be reduced. The consequences of these results could be that institutional investors should not reach a size that would lead to a controlling position within the market. The influence of trend investors should be reduced (e.g. transaction tax small enough that liquidity will not be reduced).

6. Conclusion

When tracing the causes of excess volatility and fat-tailed return distributions, herding seems to play an important role. Preceding models of stock markets (Cont & Bouchaud, Lux & Marchesi) have shown that herding and mimetic contagion are able to reproduce the stylized facts of the capital markets. The models men-

tioned create the herding behavior of the agents by dividing the agents into groups. The agents may switch between the groups, but act in concert with the other group members when buying and selling shares. We modeled mimetic contagion by introducing individual communication between heterogeneous agents that act in various types of network topologies. These networks can be distinguished by different centralization measures (closeness, betweeness, degree).

Four networks with the same number of nodes and edges, but with a different distribution of the edges were used to demonstrate how the topology itself influences the price building process. The random network and the small-world network with low centralization and two scale-free networks with higher centralization measures were used as communication networks for the agents trading in our artificial stock market. The results of our simulations indicate that rising centralization measures generate higher stock price volatility and higher distortion from the inner value.

Trend-orientated trading by uninformed agent investors jointly with information contagion in centralized networks could be one explanation for the existence of the stylized facts (like excess volatility, fat tailed return distributions and volume-volatility correlations) in real stock markets. With these simulation results we would like to complement the findings of market microstructure theory and offer an alternative to findings like in Clemons and Weber (1997). Market microstructure theory relies in gerneral on illiquidity and transaction costs to explain the stylized facts of the capital markets whereas we try to explain properties of financial prices with the help of agent behavior within networks.

These results may have implications for the understanding of real markets. The influence of major stock market players like banks, pension funds and hedge funds on the behavior of unsophisticated private investors can be seen as a potential source of misvaluations. The consequences could be to prevent insitutional in-

29

vestors from growing over a criticial size that would give them them a leadership within the market. The expression of opinions of mayor players and media could be further controlled to prevent personal interests and information avalanches that could lead to market overreactions. Retail traders should be detained from falling for short lived market trends through education.

Empirical evidence about communication networks between market participants and additional data about the behavior of unsophisticated private investors would be helpful to further harden our results. The communication network used could be tailored to measurments found in observed networks and the trading behavior of retail investors could be better represented. Such a study, even when complex und costly, would bear the benefit of a better understanding of the behavior of retail investors when trading within turbulent markets.

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